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PRACTICAL EXPERIENCES IN REFINERY CONTROL LOOP PERFORMANCE ASSESSMENT

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Abstract

The paper presents an example of the application of a control loop performance assessment technique in a refinery setting and diagnoses the causes of oscillations in flow loops. *Key words*: Process control

Introduction

Studies of the performance of single-input-single-output control loops have shown that reasons for poor performance of basic SISO loops include both poor tuning and equipment problems such as sticking valves (Åstrom, 1991; Ender, 1993; Hägglund, 1995).

Performance indices have been developed by Harris (1989), Desborough and Harris (1992) and Stanfelj *et al* (1993) which provide figures of merit for the performance of a loop. An advantage of these indices is that they can be derived during normal operations without taking loops off-line for special tests. The figures of merit may be used to distinguish between loops that need retuning, those that have a hardware fault such as a sticking valve, and those that are performing satisfactorily. Improved control yields commercial benefits while other benefits of a systematic assessment include the ease of maintenance of basic control functions and the reduction in man-hours in the trouble-shooting of control problems.

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In this paper we demonstrate applications of the control loop performance assessment technique (CLPA) proposed by Desborough and Harris (1992) to loops in a refinery. In particular, we demonstrate a strategy for determining a key parameter required by the technique. The paper emphasises the value of the spectral signature for interpretation of the control loop data and introduces a new signature that complements the spectral analysis.

Methods

Overview

Figure 1 shows a single-input-single-output feedback control loop. The key variable for CLPA is the controller error, e, given by $(sp\text{-}pv)$. If the loop is performing well it should reject disturbances, and the process variable should track the set point. These requirements imply that the controller error should have no predictable component. There should not, for example, be a steady state offset or any predictable oscillation.

Because of the dynamic nature of the process and of the controller itself it takes a

little time for the controller to achieve rejection of a disturbance or to bring the process to its set point. Thus the intent of the performance index is to determine how predictable the controller error is beyond some suitable time horizon. If the control error is predictable over this time horizon then the loop is performing poorly and, by contrast, it is performing well if the error is unpredictable over this time horizon.

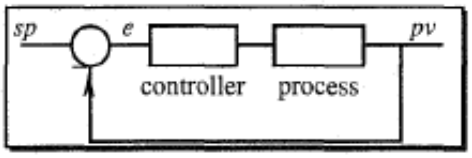

Figure 1. Feedback control loop

Theory

Desborough and Harris (1992) devised an index based upon the residuals between the measured controller error denoted by Y and a forward prediction, $\hat{y}$.

$$r(n) = Y(n) - \hat{y}(n) \qquad [1]$$

In a loop that is performing well the controller error has little predictability and the controller error contains only the random noise represented by the residuals. But in a poorly performing loop, one with a significant predictable component, the random residuals are much smaller than the controller error.

Desborough and Harris proposed the following CLPA index. A poorly performing loop has a value of η close to 1 while η for a good loop is close to 0:

$$\eta = 1 - \frac{\sigma^2_r}{mse(Y_i^2)}$$

σ^2_r: variance of the residuals
$mse(Y_i^2)$: mean square value of the controller error

The requirement for the prediction model for $\hat{y}$ is just that it is capable of capturing features in the controller error sequence. Desborough and Harris (1992) show that for typical data from process control loops an autoregression time series model that makes predictions b steps ahead is suitable:

$$\hat{y}(i+b) = a(0) + a(1)Y(i) + a(2)Y(i-1) + \ldots + a(m)Y(i-m+1) \qquad [2]$$

The above model is fitted to an ensemble of n samples of the controller error using a least squares fit procedure. The matrix $\mathbf{X}$ has the following structure:

$$\begin{pmatrix} Y(m) & .. & Y(1) & 1 \\ Y(m+1) & .. & Y(2) & 1 \\ .. & .. & .. & .. \\ Y(n-b) & .. & Y(n-b-m+1) & 1 \end{pmatrix}$$

and the vector of best fit coefficients $(a(m) \; .. \; a(0))^T$ is given by the regression equation:

$$\underline{\hat{a}} = \left(\mathbf{X}^{\mathrm{T}}\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\,\underline{\mathbf{Y}}$$

where $\underline{\mathbf{Y}}$ is $(Y(m+b) \; .. \; Y(n))^{\mathrm{T}}$.

Strategy for application to a large plant.

In a refinery there are large numbers of basic SISO feedback loops. An automated CLPA technique needs a means of providing suitable models for every loop. The autoregressive model needs certain parameters to be specified. These are:

The prediction horizon, b
The number of terms in the model, m
The sampling interval
The data ensemble length, n

The proposed strategy for making these choices for a large scale implementation relies upon a classification of control loops into a few generic types. Examples in a refinery would include liquid flow, temperature and pressure loops. It is supposed that the CLPA parameters for a few representative examples of loops of one type can be applied to all loops of that type. Such a strategy covers most cases and special cases are then addressed individually. For instance, setting the number of terms in the model to 30 has been found satisfactory for all loops studied provided different sampling intervals are chosen for each type of loop in order to capture features with time scales typical of the different types of loop.

Of particular interest is the choice of prediction horizon, b, and the strategy is briefly illustrated for that parameter.

Choice of prediction horizon

A benchmark against which control performance might be assessed is a minimum variance controller in which the elapsed time for restoration of control should be no more than the dead time of the process. MacGregor (1988) discussed minimum variance process control in detail while Harris (1989), Desborough and Harris (1992) and Stanfelj *et al* (1993) developed the CLPA index as a minimum variance benchmark by equating the quantity b to the process dead time.

In practice it is not easy to ascertain the dead time of a process from closed loop data. Since it is time consuming and costly to take loops off-line for special open loop tests, a practical implementation of the technique requires a means of determining a suitable prediction horizon from the closed loop data collected during normal process operations.

Exploration of the effects of different choices of prediction horizon on a selection of representative loops gives an insight into a suitable horizon. Rather than reflecting a parameter of the process the prediction horizon now becomes an *engineering criterion*, representing a demand made by the control engineer on the control loop; the criterion is that predictable components of the controller error should be dealt with within the specified time horizon.

Desborough and Harris (1992) also discovered cases where the prediction horizon should be different from the process dead time and MacGregor (personal communication) has commented on the theoretical consequences of a prediction horizon that is longer than the process dead time. Under these circumstances the benchmark is no longer a minimum variance controller because control actions in the interval between the dead time and the selected prediction horizon are not assessed.

In fact, it is generally accepted that the target for process control performance should not be minimum variance control (Stanfelj *et al*, 1993) because the resulting aggressive actuator actions cause excessive wear of valves and may impose unacceptable disturbances on the process. Thus the ideal value of a CLPA index is not necessarily zero when b is the true process dead time. An advantage of the use of an engineering criterion is that the target value of the CLPA index is zero in all but very special cases. This seems to be a more straightforward approach than that of determining true dead times and a non-zero target CLPA value for each loop.

CLPA signatures

Desborough and Harris (1992) and Stanfelj (1993), Kozub and Garcia (1993) made use of data signatures in order to interpret the nature of a poorly performing control loop. All reported the use of the autocorrelation of the controller error while Desborough and Harris also indicated the value of the power spectral density of the controller error.

In our work we have used power spectra of the controller error and of the residuals in order to provide an insight into the nature of a problem. The power spectra are computed by the Welch method (Welch, 1967) from a windowed fast Fourier transform

An additional signature is also presented, that of the cross-correlation of the modelling residuals from [1] and the controller errors, Y. The following comments give an insight into this cross-correlation as an estimate of the closed loop impulse response.

As mentioned, the controller error sequence is modelled as an autoregression sequence [2]. However, other time series models also suffice, for example, a model of the following form could be used:

$$Y(n) = c(0)u(n) + c(1)u(n-1) + \ldots \quad [3]$$

where the inputs $u(i)$ form a white noise sequence and the coefficients $c(i)$ form the impulse response of the closed loop transfer from the $u(i)$ to the controller error. It is well known that the cross-correlation function of the $u(i)$ and $Y(i)$ sequences gives the coefficients of the impulse response.

If it is presumed that [2] provides a good predictive model of the process then the residuals $r(i)$ from that model can be tentatively identified with the $u(i)$ sequence for the model in equation [3]. In practice some rigorous requirements concerning the whiteness of the $u(i)$ sequence may not be met. We have, nevertheless, found in many cases that such a procedure gives believable results that reinforce the conclusions from other visual signatures, and moreover, which are the same as the closed loop responses expected for the given loop tuning settings.

Results and discussion

Choice of prediction horizon

Figure 2 shows how the calculated CLPA index varies with prediction horizon for a representative flow loop. An ensemble of data collected from the loop had its CLPA value assessed repeatedly for different choices of the parameter b in equation [2].

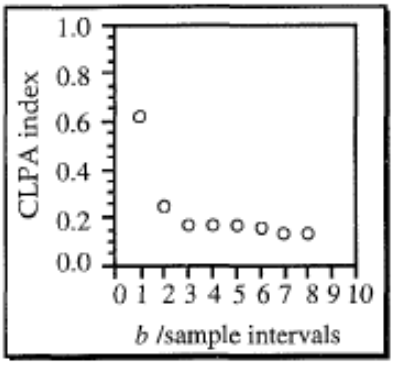

Figure 2. The effect of different prediction horizons on CLPA index

We have found such plots to be very reproducible. Most feedback loops show an initial rapid decline in the calculated CLPA index as the prediction horizon, b, increases. This in itself is unsurprising because the loop has longer to deal with any predictable component of the error signal as b increases. The majority of loops of all types, however, show an 'elbow' in this downward trend. At some value of b the downward trend stops and the CLPA index then hardly changes over a range of values of prediction horizon. Moreover, for a given type of loop (say, liquid flow loops sampled with a given sampling interval) the elbow has been observed to occur at about the same value of b.

The interpretation of the constant CLPA region is that the controller error contains a component that is predictable over a long time horizon. For example, if the controller error has a steady offset, then the CLPA index never attains a zero value because the average value of the controller error can be predicted over a long time scale. The same comment applies to a persistent oscillatory component in the controller error, which can also be predicted far ahead. A less persistent oscillation also shows a plateau, but then exhibits a further downward trend towards a CLPA value of zero. That is to say, a less well defined oscillation loses coherence and cannot be predicted beyond a finite time horizon.

It is these longer term predictable components that are of interest because they are the cause of the loss of performance of the controller. The recommendation, therefore, is to inspect plots like figure 2 for representative loops and to choose the prediction horizon so that it is within the region of constant CLPA values. In that way the CLPA examination will focus on the key problem, and moreover the calculated value of the CLPA index will be robust because it lies on a plateau. By contrast, a choice of b on the steep trend before the elbow would give values of the calculated CLPA index that would be sensitive to minor variations between loops in that steep region.

Examination of predictable component

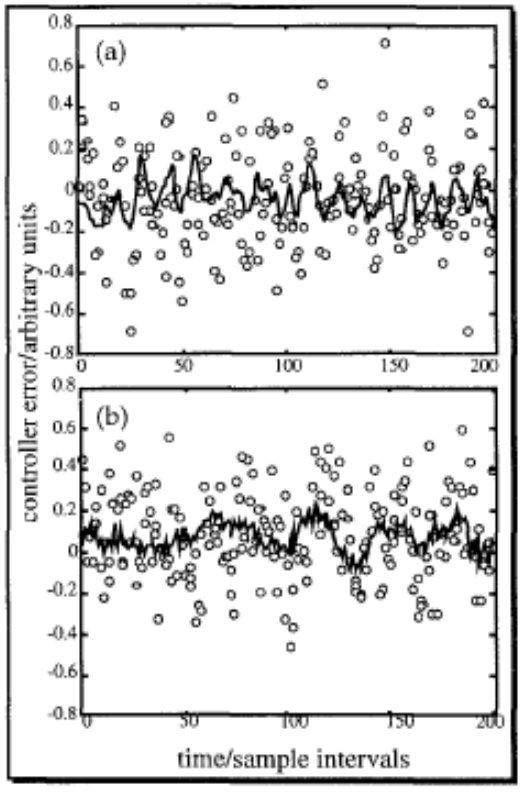

Figure 3. Controller error and predictions for a flow loop

Figure 3 shows plots of controller error and the 3-step ahead predictable component for a liquid flow loop with two different P+I controller settings. The predictable component is smaller in 3(b) than in 3(a), and the CLPA indexes for the two cases reflect this difference. The CLPA index for 3(a) is 0.16, whilst that

for 3(b) is 0.05. The question to be addressed is to establish the likely cause of the oscillatory component in 3(a).

Figure 4 presents the spectral signature for the loop in 3(a) and the estimated closed loop impulse response. In fact, both these signatures present the same information about the oscillatory feature, but in different ways.

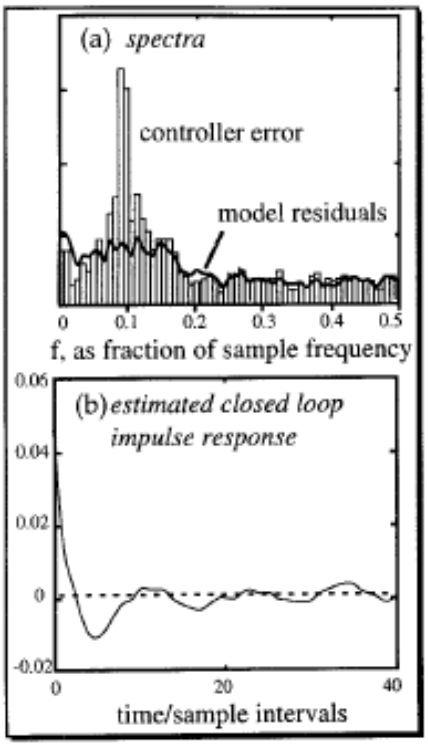

Figure 4. Spectra and closed loop impulse response for a P+I flow loop

The spectrum of the controller error (the bar plot in 4(a)) shows a significant spectral feature at about one eleventh of the sampling frequency. This is the signature of the persistent oscillation in figure 3(a), which on close examination is seen to have a period of about 11 sample intervals. It is clear that the feature is the cause of the deviation from the target zero CLPA value because the spectra of the residuals and controller error match well except in the vicinity of this feature.

In general oscillations can arise in feedback control loops because the loop is tuned in a resonant manner, because an oscillatory disturbance enters the loop and is not properly controlled, or as a result of limit cycling due to non-linearity caused, for example, by a control valve with a dead band.

What is the cause of the oscillation in this case? Figure 4(b), the estimated impulse response for the closed loop, shows a classically tuned loop with an oscillatory response and a decay ratio of approximately 25% between peaks. The time interval between zero crossings is about 11 samples, indicating the loop has a natural frequency of one eleventh of the sampling frequency. This strongly suggests that the natural frequency of the underdamped closed loop system is the cause of the persistent oscillation. The loop is ringing at its natural frequency.

While the CLPA signatures do not provide an algorithmic or a rule based approach they do provide insights that help a process control engineer to formulate theories. In this case, the nature of the closed loop impulse response suggests that the oscillations are due to an underdamped closed loop response. The hypothesis can be proved to be correct because retuning of the loop gave the closed loop impulse response in figure 5 in which the overshoot is reduced.

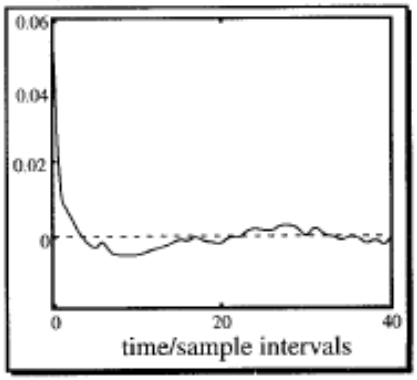

Figure 5. Estimated closed loop impulse response after retuning

Diagnosis of a non-linearity

Harris (1989) and Desborough and Harris (1992) report that a larger than expected value for the variance of the residuals may be an indication of a hardware or structural problem. Our experiences suggest that when the standard deviation of the modelling residuals exceeds about 1 or 2% of the mean value of the process variable then a hardware fault might be implicated. The example presented here is that of a flow loop with a valve having a dead band characteristic. Both the CLPA index and the standard deviation of the modelling residuals, σ_r, were large.

Åstrom (1991) has used phase plots of *sp* versus *pv* to identify valves with problems. In his work the control loop required imposed set point changes. However, the set point of a

slave controller changes continuously in a cascade configuration so an *sp-pv* plot from normal operations can indicate the nature of a valve problem.

Figure 6(a) shows the dynamic *sp-pv* plot for the control loop in question. The line on the plot is the locus of the trajectory as time passes. Its significant feature is the dead band, the horizontal segments where set point changes are not reflected in a corresponding change in *pv* . The fact that the locus tracks continuously round, roughly retracing the same path on each cycle shows that the control loop is in a limit cycle. Since the limit cycle is predictable the loop has a poor performance index. The limit cycle is of a low frequency and has a characteristic non-sinusoidal shape (Hägglund, 1994).

The spectral signature (figure 6(b)) for the loop confirms the presence of a non-sinusoidal oscillation because the spectrum of the controller error has numerous harmonics. Since the limit cycle is of low frequency, the controller error sequence must be sub-sampled in order to resolve the harmonics, in this case by using every tenth sample.

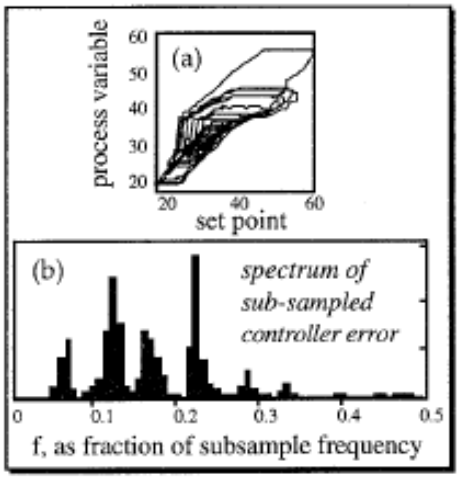

Figure 6. Dynamic sp-pv plot and spectrum for flow loop with a valve problem

We conclude from this example that the CLPA method together with spectral analysis and the *sp-pv* signature can clearly distinguish a valve problem from a tuning problem.

Conclusions

The paper has described some practical experiences with the control loop performance assessment (CLPA) in a refinery setting. An automated CLPA system has been specified and is being implemented in a BP refinery. The method is attractive because it uses data from normal process operations and does not require loops to be taken off line for special testing.

In a large process it is not feasible to tailor the algorithm to every individual loop. Rather, it is recommended that default settings be determined by inspecting a few examples of each generic type of control loop. In particular, we have shown that the prediction horizon parameter in the CLPA algorithm can be set so that the analysis highlights persistent signals present in the control loop.

A new signature that gives a visual impression of the closed loop impulse response was presented. We demonstrated that the reason for a persistent oscillation in a flow loop was a natural frequency in the closed loop response caused by underdamped tuning settings. Retuning the controller removed both the oscillatory closed loop response and the persistent oscillation. A spectral analysis was of value in the diagnosis of a suspected non-linear element in a second control loop because it showed clearly the harmonics of a non-sinusoidal limit cycle.

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